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# Credit spreads as rating event predictors

Enhancing credit rating information with market-based risk measures

Master's thesis

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## ABSTRACT - TIIVISTELMÄ

Aikaisemmat tutkimukset ovat osoittaneet, että markkinapohjaiset riskimittarit hinnoittelevat luottokelpoisuutta systemaattisesti luottoluokittajia tehokkaammin. Erityisesti bondien ja luottojohdannaisten riskipreemiot edeltävät tulevia luottoluokitusten muutoksia reagoiden nopeammin pitkäaikaisiin muutoksiin luottoriskissä. Tämä johtuu osittain siitä, että yksi luottoluokittajien tavoitteista on luokitusten vakaus, mistä syystä pitkäaikaiset luottoluokitukset arvioivat luottolaatua suhdannevaihteluiden yli. Tämän tutkielman tarkoituksena on tutkia CDS spreadien sekä bondien G-spreadien ennustevoimaa suhteessa tulevaisuuden luokitusmuutoksiin, sisältäen myös muutokset luokitusten näkymissä (outlook). Otos koostuu suurista globaaleista investment grade –pankeista ja täten tulokset ovat arvokkaita erityisesti pankkiriskin alalla. Yksikään aikaisempi tutkimus ei ole tarkastellut näin homogeenista ryhmää vaan aikaisempien tutkimusten otokset ovat sisältäneet myös ei-finanssiyhtiöitä sekä valtioita.

Spreadien potentiaalinen ennustevoima havainnollistetaan esittelemällä näiden ominaisuudet yksityiskohtaisesti sekä vertailemalla niitä keskenään. CDS- ja G-spreadin valinta perustellaan ja lisäksi luottoluokitusten yleisluonne käydään läpi. Spreadien ja tulevien luottoluokitusmuutosten välistä suhdetta tutkitaan logistisen regression avulla käyttäen selittävänä muuttujana viivästettyjä kuukausimuutoksia spreadeissa. Aikaperiodit eri otoksille vaihtelevat välillä 2006-2020 CDS-sopimuksille sekä välillä 2011-2020 bondeille. CDS-datan osalta ennustevoimaa tutkitaan erikseen myös lyhyemmällä periodilla jättäen finanssikriisin purkautumisen tarkastelun ulkopuolella. CDS- sekä bondidata on kerätty Bloombergilta ja luottoluokitukset Standard and Poor’silta.

Tulokset osoittavat, että sekä CDS- että bondimarkkinat hinnoittelevat etukäteen tulevia luokitusmuutoksia. Tämä tapahtuu molemmilla markkinoilla lähes samanaikaisesti, noin 4-6 kuukautta ennen tulevaa luokituksen tai luokitusnäkymän muutosta. Tämä pitää kuitenkin paikkansa vain negatiivisten muutosten suhteen eikä positiivisten luokitusilmoitusten yhteydessä havaita selvää tilastollista merkitsevyyttä. Spreadit eivät liiku tasaisesti ajassa sopeutuessaan tulevaan luokitusmuutokseen. Ne reagoivat ensin x kuukautta ennen muutosta eivätkä kaikki seuraavat luokitusmuutosta edeltävät kuukausimuutokset spread-tasoissa välttämättä indikoi tulevasta luokitusilmoituksesta tai ole linjassa riskin muutossuunnan kanssa.

**AVAINSANAT:** credit rating, credit spread, bank risk, CDS spread, G-spread

# 1. INTRODUCTION

One of the main information sources for firms' credit quality and financial health is credit ratings assigned by credit rating agencies. The big three rating agencies, Moody's, Standard and Poor's and Fitch, assign credit ratings for corporations and their debt securities to reflect information about the companies' ability to pay back their debt. The ratings also represent an implicit forecast of the probability of default and are important pieces of information for all creditors and parties who have net exposures regarding the debtor. Existing literature has shown that the information included in credit ratings, rating outlooks and their changes is somewhat predicted by market data, suggesting that credit rating changes, and thus changes in future prospects regarding a company's financial health, can be predicted by utilizing market-based measures in credit risk analysis (see Hull, Predescu & White 2004; Rodríguez, Dandapani and Lawrence 2019).

Credit rating changes fail to provide exclusively new information for several reasons. Rating agencies appear to apply a through-the-cycle (TTC) approach when assigning credit ratings, where they intend to look beyond single business cycles and capture a more long-term and permanent component of credit risk (Kiff, Kisser & Schumacher 2013). This is also explicitly confirmed by the rating agencies themselves (Altman & Rijken 2004). On the contrary, banks' internal risk models use a point-in-time approach (PIT) where a more short-term and temporary credit risk component is included in the assessment (Altman & Rijken 2006). As changes in the general economic environment can be expected to affect a company's financial soundness and creditworthiness, it is reasonable to consider also cyclical variation in credit risk.

Agency ratings filter out cyclical fluctuations in credit quality, which are considered temporary, in order to achieve stability in their ratings (Basel 2000). Investors have a preference for relatively stable ratings arising for instance from governance rules, as excessive rating changes can lead to higher transaction costs when portfolio allocation is rating-based, among several other reasons (Löffler 2013). This desire for stability, though reasonably justified, together with the fact that firm-specific fundamental financial data is published only once in every quarter, has led to critique towards the information content of credit ratings. This study aims to demonstrate that a more point-in-time approach is superior to the agency-applied through-the-cycle approach in determining the credit quality of a debtor.

## 1.1. Purpose of the study

The purpose of this study is to see if market spreads precede ratings systematically and if so, the aim is to identify any potential differences between how bond and derivative markets predict changes in credit ratings and thus in credit quality. From the point of view of a credit analyst or a portfolio manager, it is of great interest to find out which particular market leads the price discovery of credit quality. The emphasis is on credit default swap (CDS) spreads and bond credit spreads, namely G-spreads (government spread), though other bond spreads are also covered in the theory section for comparison. Rating outlooks and watches are incorporated into ratings to obtain adjusted ratings, so that the information value from rating agencies is maximized. The terms rating *watch* and *review* are used indistinguishably in this thesis.

Firms under analysis are limited to banks as the intention of the study is to focus on risk measures relevant for measuring the credit risk of financial counterparties. If the markets are proven to anticipate credit rating changes, the length of preceding anticipation is also investigated. In the logistic regression model applied, monthly spreads lagged up to 9 months are used to determine how long beforehand bond and derivative markets can price future rating changes.

## 1.2. Motivation of the study

Jacobs, Karagozoglu and Peluso (2010) show that a significant amount of the difference between CDS spreads and credit ratings cannot be explained by either market or firm-specific variables, despite arguing that CDS spreads should theoretically mirror “the pure credit risk of a firm”. Hull et al. (2004) demonstrate among others that credit rating changes are anticipated by the market and information regarding changes in credit quality can be found in CDS spreads prior to the rating change announcements, which indicates that market-perceived credit risk is more up-to-date than the risk implied by the rating itself. This justifies a more market-based risk model as credit ratings seem to be inferior measures of credit risk and do not solely contain enough information about credit quality. Therefore, market’s perception of risk is studied in order to determine if it mirrors credit risk more efficiently than credit ratings alone.

This thesis complements the work of Rodríguez et al. (2019) who study the predictive power of CDS spreads on sovereign ratings. Their sample includes sovereigns of very different credit quality and one could argue that their results may be driven by the most volatile subclasses of sovereigns in the sample. In this study, all of the sample banks are investment grade rated making the sample more homogeneous, and in addition, bond credit spreads are also included in the analysis to see how well the bond market prices future rating events.

This thesis examines how the credit risk of world’s biggest financials is priced in both derivative and bond markets, as most of the world’s biggest banks are investment grade rated. Contrary to existing literature, this thesis provides valuable insight especially to the field of bank risk analysis. As Tong (2015) notes, modeling default probabilities for financials has traditionally been difficult compared to non-financial firms.

## 1.3. Structure of the study

This thesis consists of three main sections. The first main section covering chapters 2 and 3 is comprised of the theoretical background, where the basic mechanics of different credit spreads are explained along with their key strengths and weaknesses as measures of fundamental credit quality. Differences between them are addressed as well with the help of previous literature. The theory section will also discuss the basic rationale behind credit ratings and some of their key characteristics. In the first chapters emphasis is on fundamental financial theory, rather than the details and applicability of the findings of this study. The second main section will describe the data in detail and introduce the methodology. These are covered in chapters 4 and 5. The last main section starting from chapter 6 discusses the empirical results of the study and concludes the whole thesis.

## 2. CREDIT SPREADS AS MEASURES OF CREDIT RISK

Credit risk and liquidity risk have traditionally been regarded as the two main components of risky bond yield spreads. For bonds of large global banks such as those studied in this thesis, credit risk can be considered to be main driver of the overall credit spread, excluding times of excessive market disruption when the order book for a security can become dominated by continuously decreasing ask quotes and liquidity dries up. Liquidity premium of a bond, measured in basis points, is to no surprise generally heavily negatively correlated with the amount of active dealers, making credit spreads better measures of fundamental credit quality the better the liquidity of the security (Ericsson & Renault 2006: 2232).

Whether bond and CDS markets do or do not restore liquidity symmetrically during a crisis period, it is nonetheless meaningful to investigate both CDS and bond spreads. If spread changes are significant predictors of future rating events, it should not be due to a liquidity factor, as decreasing market liquidity in itself does not trigger rating events *without* changes in the underlying company's credit quality. Since the creation and expansion of credit derivatives, CDS spreads have become increasingly important market-based measures of credit risk. Bühler and Trapp (2009) show that CDS contracts are mainly used for hedging credit risk, while bonds as traditional investment vehicles can by their nature be used to a large extent for several other purposes. This is why CDS spreads are examined in addition to bond-derived credit spreads. Also, as the CDS spread is not a yield per se, it should not be as easily affected by sharp fluctuations in benchmark risk-free rates.

Chen, Lesmond and Wei (2007) find that more illiquid bonds have higher credit spreads. However, the liquidity premia in both CDS and bond spreads have been found to be roughly of the same size (Bühler & Trapp 2009). Tang and Yan (2007) find similar results and argue that the parallel relationship regarding the size of the liquidity component of the spread holds for both Treasury and corporate bonds. This implies that idiosyncratic liquidity does not significantly affect the relative size of the liquidity premium, as Treasuries can be considered on aggregate more liquid than most corporate bonds.

Contradicting findings can also be found in previous literature. Calice, Chen and Williams (2013) demonstrate that during the euro crisis liquidity in bond markets dried up and bond spreads became more driven by liquidity premia. However, decreasing liquidity in itself does not necessarily result in divergence of the spreads, since Gyntelberg, Hördahl, Ters and Urban (2017) discover that during the euro debt crisis, the difference between CDS and bond spreads increased in markets where liquidity increased simultaneously.

## 2.1. Differences in bond and CDS spreads

Bond and CDS spreads do not always measure credit risk unambiguously, even though they both should theoretically represent a compensation for possible default in a comparable manner. This can be seen in the CDS-bond basis, which is the difference between the quoted spread on a CDS contract and the bond-derived spread, both instruments having the same reference entity (Bai & Collin-Dufresne 2019; De Wit 2006). As the liquidity premium should be approximately of the same size across these two asset classes, existence of such a basis indicates that risk is priced differently in bonds and swaps. It is unclear whether this widening of the basis is due to bond investors' different perception of the true underlying credit risk, or due to other factors, such as possible imbalance in bond supply and demand.

In fact, even the choice of the risk-free benchmark curve can have an effect on the bond credit spread and thus the CDS-bond basis. Usually the risk-free benchmark curves derived from government bond yields and from swap rates are not identical, giving different term structures for risk-free rates. This can be due to many factors, such as a high demand on safe haven bonds suppressing their yields (Klingler & Sundaresan 2019), or other factors in the swap or interbank market.

CDS-bond basis is limited by an arbitrage opportunity, as interbank traders can buy a bond paying LIBOR + spread, fund the position with LIBOR and buy a CDS to eliminate the default risk. If the CDS spread is lower than the bond spread, the trader pockets the spread basis as a risk-free return, assuming that the CDS is collateralized eliminating counterparty risk. This arbitrage limits the basis to some extent and makes the spreads closely linked (Klingler & Sundaresan 2019).

The strength of using a swap curve, such as LIBOR or EURIBOR curve, is that it is more generic than a bond yield curve, which is issuer specific and constructed of notably less underlying instruments, making bond yields more sensitive to price fluctuation. However, also interbank rates contain implicit credit risk (Klingler & Sundaresan 2019). This means that it is very plausible, that bond spreads are driven by factors in the swap market and money market, not the bond market. This can be seen in Libor-OIS and Euribor-OIS spreads, as well as in the TED spread. After the financial crisis, many kinds of basis spreads have emerged in fixed income markets showing that interbank lending is nowadays viewed with much more uncertainty (for details on these basis spreads, see Gallitschke, Seifried & Seifried  2017).

OIS stands for *overnight indexed swap* and OIS rates represent fixed rates swapped against the OIS curve, which is constructed based on an overnight rate, such as ESTR (will replace Eonia completely in 2022). OIS rates can be considered the best proxies for risk-free rates, as credit risk is minimal in overnight lending. During the last decade, the implicit credit risk in money market rates has become prominent, especially during periods of high uncertainty.

Figure 1 plots three different basis spreads between April 2011 and September 2020: EURIBOR-OIS spread, TED spread, and USDLIBOR-OIS spread, all with a 3-month tenor. EURIBOR-OIS spread is the difference between 3-month EURIBOR and 3-month EUR OIS rate, TED spread is the difference between 3-

month USD LIBOR and yield on the 3-month Treasury bill, while USDLIBOR-OIS represents the spread between 3-month USD LIBOR and the respective USD OIS rate. One can see from Figure 1, that the spreads between 3-month money market rates and overnight-based rates, as well as rates obtained from bond yields, can be several dozen basis points (bps), reaching over 50 bps in turbulent periods. This clearly confirms that the underlying benchmark curve can have a strong impact on the size of credit spreads.

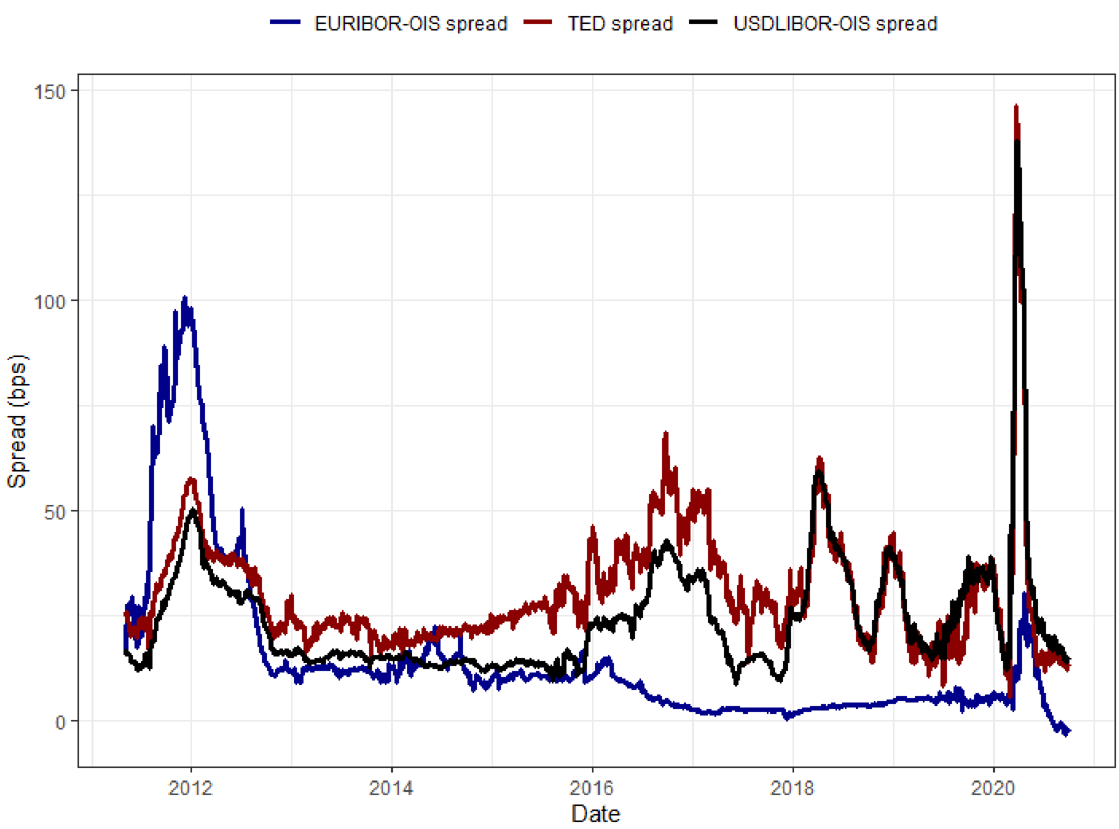


**Figure 1.** Basis spreads in risk-free rates.

For previous reasons, in this study the focus on bonds is on the G-spread, which is the difference in yield compared to an almost risk-free government bond. Other bond credit spreads are also presented in this chapter for comparison and their advantages and disadvantages are evaluated. One can later on clearly see that there is no perfect bond derived measure of credit quality and the choice of spread can vary depending on the exact underlying interests. However, it is concluded in this chapter, that the G-spread is overall the most stable and thus the purest measure of credit quality from all common bond spreads, as it is not distorted by drivers on the swap market (the z-spread would also be a good choice, if calculated against the government spot curve and not the swap curve).

## 2.2. Yield-derived spreads

G-spread is a yield-derived spread and the use of it is justified in this chapter. Overall, bond spreads computed from yield to maturities (YTM) undergo same problems as YTM itself, most notably that the yield on a given security is realised only if held to maturity and that possible coupons can be reinvested at exactly the same rate, implying essentially a flat yield curve (O'Kane & Sen 2005; Klein & Stellner 2014). Usually referred to as the yield spread, the basic YTM-derived credit spread is simply (Gunay 2019:162):

(1) $$S = Y - Y_{rf}$$

where:

$Y$ = is the yield to maturity of the underlying bond,

$Yrf$ = is the yield to maturity of a risk-free benchmark bond.

Another setback of the yield spread is that it may be difficult to find a default-free bond with matching maturity, when assessing the credit risk of a corporate bond. This maturity mismatch can be tackled by using an interpolated spread (i-spread), where the YTM of a risky bond is compared with a yield interpolated from two benchmark bonds with different tenors (O'Kane & Sen 2005). While the i-spread solves the problem of maturity mismatch, there is no real reference security behind the estimated risk-free yield. Yet, yield-derived spreads escape the discrepancies in risk-free curves constructed from the swap market and from the bond market, as yield-derived spreads are always comparing a bond-based rate on another bond-based rate. G-spreads collected for our sample are fixed 5-year points on respective issuer spread curves (in order to improve comparability with CDS spreads), and are therefore interpolated spreads, as there are most likely no outstanding bonds with an exact maturity of 5 years either from the issuer or the risk-free entity.

### 2.3. Z-spread and option-adjusted spread

In essence, the option-adjusted spread is the constant basis point measure added on top of a risk-free spot curve, such as the government spot curve, when adjusting a risky bond's value equal to its market price by also removing the price effect of a possible embedded option (Cavallo & Valenzuela 2010; De Wit 2006). The generic idea behind it resembles to that of the zero-volatility spread (z-spread) as it is a constant spread on top of a risk-free discount rate, though the concept and calculation of OAS is a bit more complex. First, the Z-spread is the parallel shift of a benchmark curve, which makes the bond's value equal to its market price, when cash flows are discounted with this shifted curve (see Figure 2).

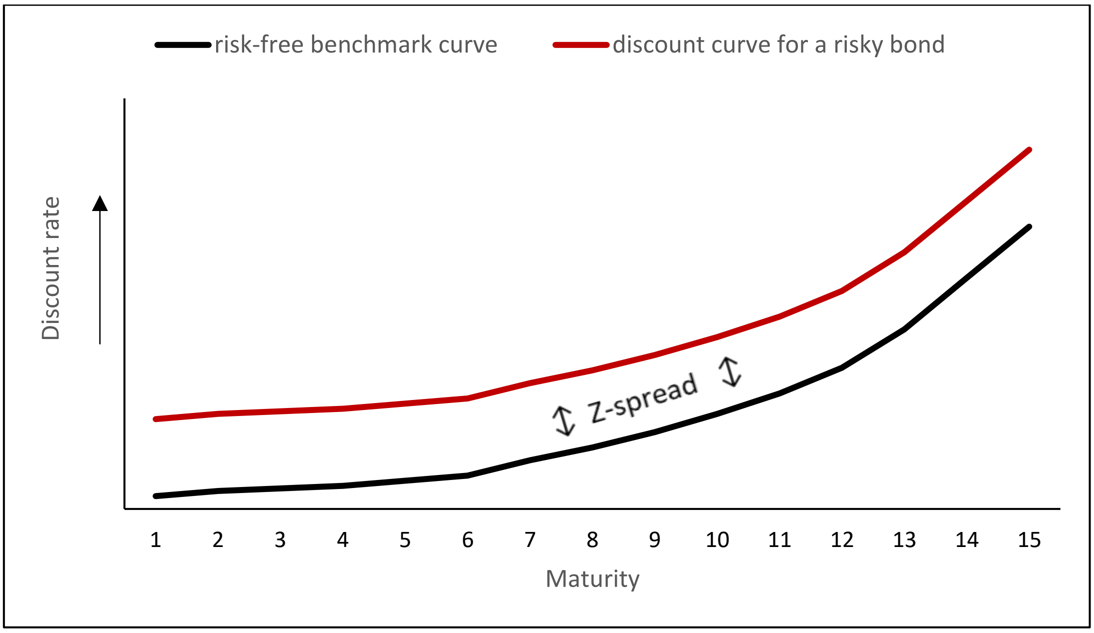


**Figure 2.** Zero-volatility spread (O'Kane & Sen 2005).

Z-spread is solved from the following equation (O'Kane & Sen 2005):

(2) $$P = \sum_{t=1}^{n} \frac{CF_t}{(1+F_t+Z_{spread})}$$

where:

$P$ = market price of the bond,

$CF_t$ = cash flow at time t,

$F_t$ = benchmark discount rate at time t.

OAS is very similar to z-spread and in case of an option-free bond, OAS equals the z-spread. Unlike the z-spread, OAS eliminates the possible value of optionality making credit spreads of bonds with and without embedded options comparable. In order to do so, the option must be valued with a dynamic option-pricing model. This causes OAS to be model-dependent, i.e. the spread is somewhat contingent on how the applied model values the option, which is its shortcoming. However, this dependency exists only for bonds with embedded options.

The relationship between the two spreads can be expressed as: z-spread = OAS + option cost (Fabozzi 2008:79). In case of a callable bond, the option is of negative value for an investor and lowers the market price, leading to a higher z-spread vs. a similar option free bond. It is evident that the z-spread does not anymore reflect the fair credit spread in a callable bond, as the lower market price is compensation for call risk, not credit risk. Thus, a higher demanded return premium is not credit-related but rather accounts for the possibility that the bond is redeemed early and investors lose their original yield. Due to this exact risk, yield to call (YTC), which is the traditional yield adjusted for the option effect, is used instead of YTM to evaluate the yield on callable bonds.

We now know that the difference of these two spreads lies in the option value. It is important to know that bond options account for interest rate volatility. As the forward rates are not considered to remain constant, i.e. the forward rates will not necessarily match future spot rates, simulation of multiple interest rate paths along the maturity of the bond is required. This leads to more than one possible discount rate for every time point that matches a cash flow.  OAS is the constant spread added to interest rates on every possible interest rate path.

Hence, the z-spread can be considered to be a zero-volatility OAS, as in the absence of interest rate volatility, there is only one interest rate path (the actual benchmark curve). In this case, the calculation of OAS is identical to the one that is performed in order to obtain the z-spread. (Fabozzi 2008: 77-79). For bonds with embedded options, the higher the interest rate volatility, the higher the difference between z-spread and OAS. This can be quite intuitively deduced from: z-spread = OAS + option cost, keeping in mind that higher interest rate volatility increases the value of the option (see Hull 1996). As OAS is by nature unaffected by changes in the option value, it stays constant in the equation and z-spread is the variable that adjusts to equilibrium.

OAS takes into account the term structure of interest rates, and in that sense is a more refined measure of credit risk than a YTM-based yield spread. However, if the benchmark curve is a swap curve, z-spreads and OAS spreads can be significantly affected by demand in swap contracts, as well as credit premia in interbank rates.

## 2.4. Asset-swap

Although the term “asset swap” refers to a swap contract, the position is linked to a cash bond and it combines the bond position with a swap, making its spread closely connected to the underlying bond. Duffie (1999) states that regarding cash instruments, the spread of a par floating rate bond is most comparable with the premium paid on a CDS contract. This is fairly straightforward as the spread added on top of the reference rate is explicitly quoted in the bond terms and as the bond is priced at par, this implies that the cash flows are discounted with a spread equal to the coupon spread over the reference rate. That is, the coupon spread is the bond’s z-spread, given that the reference rate is used as the risk-free rate in discounting. Unfortunately, floaters are less commonly traded than fixed-rate bonds (De Wit 2006), which complicates the search of comparable bonds. This is why assets swaps are of value, as they determine a fixed bond’s fair value in the context of a floating rate plus the spread.

An asset swap is a synthetic position combining a fixed coupon bond and a traditional plain vanilla interest rate swap (IRS). It enables investors who are long on a fixed rate bond to transform the fixed coupon payments into floating cash flows, while getting an explicit measure of the bond’s credit premium over a floating benchmark rate. In an ASW the bond holder engages in a swap where he or she pays the fixed bond coupons and receives a floating rate plus the ASW spread. This spread depends on the bond’s market price and might not be equal to the spread on a vanilla IRS against the bond’s fixed coupon rate. Hence, the

ASW spread can be interpreted as a yield-like figure, as it is also an indicator of relative value in addition to a pure credit measure.

An ASW is constructed as follows:

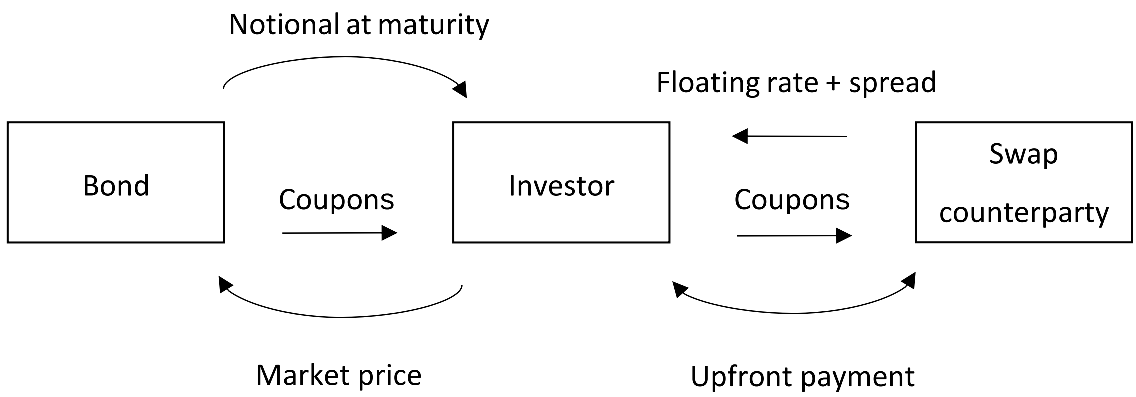


**Figure 3.** Mechanics of an asset swap (Gyntelberg et al. 2017).

From Figure 3 we can see that the upfront payment can be paid either by the bond investor or the swap counterparty in the ASW. This is determined by whether the bond is trading at premium or discount. One of the swap counterparties pays the market price difference to par (100-P can be either negative or positive). It can be thought of as a netting mechanism, as it equalizes the assumed initial notional payments, which are not in fact made. This logic is analogous to an IRS, where the notionals are not exchanged as a vanilla IRS uses par notionals, which would net each other out in terms of value, leading to unnecessary cash transactions if executed.

### 2.4.1. Asset swap spread

The ASW spread can be solved from the following equation that demonstrates the valuation of an ASW trade at initiation (Choudhry & Lizzio 2015:9).

(3) $$PVfixed - \left(PVfloat + ASW_{spread}\right) + (100 - P) = 0$$

where:

*PVfixed* = the present value of all fixed rate (coupon) payments,

*PVfloat* = the present value of all floating payments tied to a reference rate,

$ASW_{spread}$ = spread added on top of the reference rate for every floating payment to reach equilibrium,

*P* = market price of the bond. Difference to par (100-P) is paid at the start of the contract as an upfront payment.

As can be seen from the equation above, the floating leg spread is the only non-obtainable term when the discount curve and the reference rate forward curve are determined. It is important to note that the bond's market price has a direct effect on the spread. If the bond trades exactly at par, there is no upfront payment (100-P) and the notional amounts would not affect the value or spread of the ASW. Based on this logic, the final notional exchange cash flows are neither affecting the valuation, as they are equal and net each other out. For the same reason notional amounts are not exchanged in traditional IRS contracts, as explained before. However, if an upfront payment exists, it affects the ASW spread as the size of a possible upfront payment is based on a market price, which is easily observable. This leaves the spread as the only variable that is not given and hence needs to be solved.

Essentially, the asset swap spread gives an accurate measure of the credit risk of a hypothetical floater trading at a price equal to the fixed rate bond in the asset swap package. This would not be observable from a position consisting of a discount or premium cash bond and a plain vanilla IRS, even though the resulting hedge would be very similar as the investor would buy the bond at market price, receive floating rate coupons, and receive notional at maturity. Likewise, the coupon spread of a floating rate bond would be a measure of current credit premium only if the bond is priced at par, as for par bonds the discount rate equals the coupon rate. For a discount or premium floater, the coupon spread only tells the credit premium at the time of issuance, and the divergence from par would indicate a realised change in the issuer's credit quality. If one tries to determine the credit spread of a fixed-coupon non-par bond through an IRS, the spread of the floating leg would only reveal the value of the fixed coupon rate relative to the current term structure, as an IRS is valued using par notionals.

It is worth noting that the ASW spread is the only traded spread of the ones mentioned above, while the others are artificial and more implicit measures of credit risk. For example O'Kane and Sen (2005) as well as De Wit (2006) argue that due its cash flow characteristics, similar to CDS contracts, ASW spread is the most comparable bond-derived measure when examining credit risk pricing between bond and derivatives markets. Yet, ASW spread is sensitive to changes in interest rate regimes even after considering possible changes in liquidity (Aussenegg, Götz & Jelic 2016; Duffie 1999). This diminishes the conclusions of O'Kane and Sen (2005) and De Wit (2006), as the interest rate environment has fundamentally changed after the financial crisis and thus the ASW spread has become vulnerable to new distorting factors.

ASW spread is also affected undesirable, when the underlying bond is priced with a deep discount or premium (Aussenegg, Götz & Jelic 2016; Duffie 1999). Large movements in the yield curve can contribute to the CDS-bond basis because ASW spreads are linked to the underlying bond's value relative to par. When the bond price diverges significantly from par, the ASW-based CDS-bond basis tends to increase. As discussed above, the disparities between bond and swap markets has disturbed both ASW and z-spreads in the last decade.

Supply and demand on bond markets also play a role in credit spreads. If a bond is underpriced, it trades with an artificially high credit spread. This might be observed during high market distress, when extreme flight to safety occurs and bonds are being sold as investors are building up their cash positions. When demand is notably high for a certain security, the opposite occurs resulting in lower credit spreads that would be reasonable based solely on credit quality. When looking at how all of these different spreads have behaved during the last decade, one can nonetheless conclude that yield-derived spreads have showed the best stability and overall performance, if one thinks how credit spreads should intuitively move. For one, negative bond spreads are poor reflections of credit quality, even for investment grade companies. This results in the choice of G-spread for the bond credit spread used in this thesis.

## 2.5. Credit default swap

Credit default swap is a derivative contract, where the buyer pays an annual premium, the CDS spread calculated on the notional amount, to the seller and in turn the seller is obliged to compensate the buyer, if the underlying asset defaults (Bodie, Kane & Marcus 2009: 810). The amount of compensation is determined in the contract as are the terms of a default event. CDS contracts are used mainly for credit risk transfer, but also for mark-to-market risk, as an optimal hedge ratio balances out valuation volatility in underlying bonds. CDS constracts are also used for synthetic bond investments, as the net exposure to a bond can be adjusted by trading CDS contracts, which may prove cheaper than trading the bond itself (Culp, Van der Merwe & Stärkle 2016).

CDS spread is composed of two main components: the probability of default and the loss given default (LGD), or recovery rate, which is *1-LGD.* Without major changes in capital structure and debt hierarchy or the magnitude of external support at default, LGD can be seen as the more stable component, meaning that the probability of default is the main driver of CDS spreads. A default event is described in contract terms in detail and does not necessarily mean bankruptcy of the underlying entity.

Most CDS contracts are settled physically. After a credit event, the contract seller pays the difference between par notional value and the recovery rate, which is the price the bond is trading at after the default event, and the contract buyer delivers a bond from a basket of eligible obligations (Culp et al. 2016). This means that contracts are not linked to a single underlying obligation, but rather to a pool of eligible bonds. Another option is to settle the contract in cash, which is much more rare (Culp et al. 2016). To conclude, CDS is an effective way to transfer the credit risk to the seller, which is why the CDS spread paid for compensation is conceptually a very pure measure of credit risk.

### 2.5.1. Credit default swap spread

The spread (or price) of a CDS contract is linked to the probability of default as follows:

(4) $$PD = \frac{CDS_{spread}}{(1-R)}$$

where:

*PD* = annual probability of default,

$CDS_{spread}$ = spread paid by the buyer,

*R* = recovery rate.

Several factors motivate the use of CDS spreads as risk proxies. Some previous studies argue that the overall liquidity in CDS markets increases relative to bond markets, when a systemic crisis emerges (Calice, Chen & Williams 2013). Calice, et al. (2013) examine credit spreads during the Eurozone sovereign debt crisis and perceive a narrowing of bid-ask spreads in CDS contracts when overall credit spreads increased. An increase in liquidity should in theory result in more efficient market pricing. Gunay (2019) argues that since CDS contracts are unfunded and there are no restriction on short selling, they react faster on new information. Longstaff et al. (2005) find that bond credit spreads can be affected by factors that are not default-related, such as liquidity. This should not be as much of an issue in CDS contracts, at least for big global banks studied in this thesis.

Another important fundamental characteristic of CDS spreads also supports their use as “pure” risk measures: the absence of the risk-free rate. Oppositely to bond yields, CDS quotes do not incorporate the risk-free rate component and are therefore unaffected by changes in the benchmark curve, while the risk-free rate is implicitly included in bond yields. Although bond credit spreads, such as OAS, are constant basis-point measures added *on top* of a risk-free yield curve, they can still be undesirably affected by changes in risk-free rates. This is because bond yields and consequently yield curves are derived from bond prices, and risk-free rates are included in the calculation process of valuing a bond. As forward rates are also derived from bond market prices, large shifts in the forward curve can distort bond credit spreads, as multiple instruments are simultaneously adjusting to the market’s new perception of future risk-free rates.

## 3. CREDIT RATINGS

Credit ratings assigned by credit rating agencies are one of the most well known sources of credit quality in the market. Relatively good standardization, simplicity and transparency make them ease to interpret and they have become the third-party benchmark for evaluating credit, ever since John Moody published the first ratings in history in the early 20th century. The field of third-party credit analysis is strongly occupied by the three big agencies: Moody's, Standard and Poor's (S&P), and Fitch. In addition to aiming for accuracy, rating agencies try to rate credit quality "through the cycle"

On aggregate, credit ratings have been relatively good predictors of default and financial distress (Altman & Rijken 2006; Kiff et. al 2013). Yet, existing literature has widely recognized that the information related to rating announcements is lagged compared to market data and many of the previous studies have examined the predictive power of CDS spreads in both Europe and the US (Rodríguez, et. al 2019; Jacobs et al. 2010; Hull et al. 2004). Investigating this is justified, as rating agencies smoothing the ratings with a TTC-approach leads to lower performance in predicting default, as Kiff et al. (2013) reveals.

Rating agencies assign various different ratings for one issuer and the debt it has issued, both for short-term and long-term. It is usual for an issuer to have distinct issuer ratings, senior unsecured ratings, bank deposit ratings, derivative counterparty ratings etc. In this thesis, long-term issuer ratings are used. Ratings from Fitch and S&P follow an identical scale, while Moody's uses a slightly different denotation on its rating scale, which is still fully comparable to the ratings of Fitch and S&P. Whoever the rater, the fundamentals of a credit rating are still very much the same. Table 1 presents the long-term issuer credit rating scales of the three big agencies.

**Table 1.** Long-term issuer credit rating scales.

| | S&P | Moody's | Fitch |
|---|---|---|---|
| Investment grade | AAA | Aaa | AAA |
| | AA+ | Aa1 | AA+ |
| | AA | Aa2 | AA |
| | AA- | Aa3 | AA- |
| | A+ | A1 | A+ |
| | A | A2 | A |
| | A- | A3 | A- |
| | BBB+ | Baa1 | BBB+ |
| | BBB | Baa2 | BBB |
| | BBB- | Baa3 | BBB- |
| High-yield | BB+ | Ba1 | BB+ |
| | BB | Ba2 | BB |
| | BB- | Ba3 | BB- |
| | B+ | B1 | B+ |
| | B | B2 | B |
| | B- | B3 | B- |
| | CCC+ | Caa1 | CCC+ |
| | CCC | Caa2 | CCC |
| | CCC- | Caa3 | CCC- |
| | CC | Ca | CC |
| | | | C |
| Default | SD | C | RD |
| | D | | D |

As discussed before, in addition to actual rating changes, rating agencies publish reviews and outlooks, which essentially are indicators for possible future upgrades or downgrades. By doing this, rating agencies try to distribute new information to all relevant parties without immediately changing the rating itself, thereby embracing their stability policy. Altman and Rijken (2007) as well as Hamilton and Cantor (2004) show that rating reviews and outlooks are able to explain most of the differences between actual ratings and ratings implied by CDS spreads, which have been shown to predict future changes. Hull et al. (2004) find that in general CDS spreads are able to explain better negative rating events, positive events yielding much less significant results.

According to existing literature, CDS spreads seem to predict future rating changes and they do so more efficiently than bond prices, leading the price discovery together with stock prices (Lee, Naranjo & Velioglu 2018). To extend the price discovery process even further, implied volatility seems to be a good predictor of future CDS prices, though the explanatory power decreases the better the credit rating of the firm (Cao, Yu & Zhong 2010). However, contradicting results have also been found as Löffler (2013) argues that credit ratings actually predict future changes in market-derived probabilities of default.

Nevertheless, it seems that stakeholders are able to do a more up-to-date risk assessment by utilizing reviews/watches, outlooks and CDS spreads, which supports the superiority of the PIT approach. Carvalho, Laux and Pereira (2014) demonstrate that during recessions ratings are more volatile, which implies that rating agencies in fact do incorporate cyclical measures in their ratings. But most importantly, they show that ratings are also more accurate during negative business cycles, again supporting a more market-based risk model. However, the information value in outlooks and reviews varies over time, most likely because rating agencies do not fully standardize credit risk information when assigning these (Altman & Rijken 2017). This favors market data as an information source. Market prices also adjust to new information faster than the agency rating process, despite the information value in outlook and review announcements.

# 4. DATA

Main data consists of CDS spreads, bonds' G-spreads and credit ratings, including outlooks and rating watches. Monthly observations are used in regressions and therefore every variable is an end-of-month value. This concerns both rating values and credit spreads. Every one of the 29 banks are classified as investment grade based on their rating and all originate from a developed market. Sample banks are distributed globally over Europe, Asia and North America. 27 of the 29 banks are among the top 100 world's largest banks ranked by total assets, listed by S&P on April 2020 (Zarmina 2020).

## 4.1. Credit spreads

CDS prices for 29 banks are examined from October 2006 to September 2020. Bond data sample consists of 24 banks and the period ranges from April 2011 to September 2020. Bond data is studied as one sample, whereas the CDS data set is examined both for the whole sample period and also for a shorter period starting from October 2010 (including lagged CDS spreads from the start of the year). Creating an additional CDS data period for post 2009 gives a more comparable data set in regards to the bond data, as the most crucial months of the financial crisis are omitted. Periods of financial distress are still desirable when investigating rating movements, as they then tend to occur more often (Carvalho et al. 2014). All of the 24 banks within the bond data are also included in the sample of CDS data.

When looking at both CDS spreads and G-spreads, one can see that the original spread values are not normally distributed and the distribution resembles more a log-normal distribution. This is expected as extreme movements in spreads become less likely as the absolute value approaches zero. Bond spreads could potentially be negative, but due to several reasons mentioned in the previous chapter while comparing different spread measures, G-spreads are expected to stay positive and indeed no negative values are perceived in the data. Spread data is transformed into log values for the regressions. Distribution of the original spread values can be seen in Figures 4 and 5 (spread values on x-axis are in basis points).

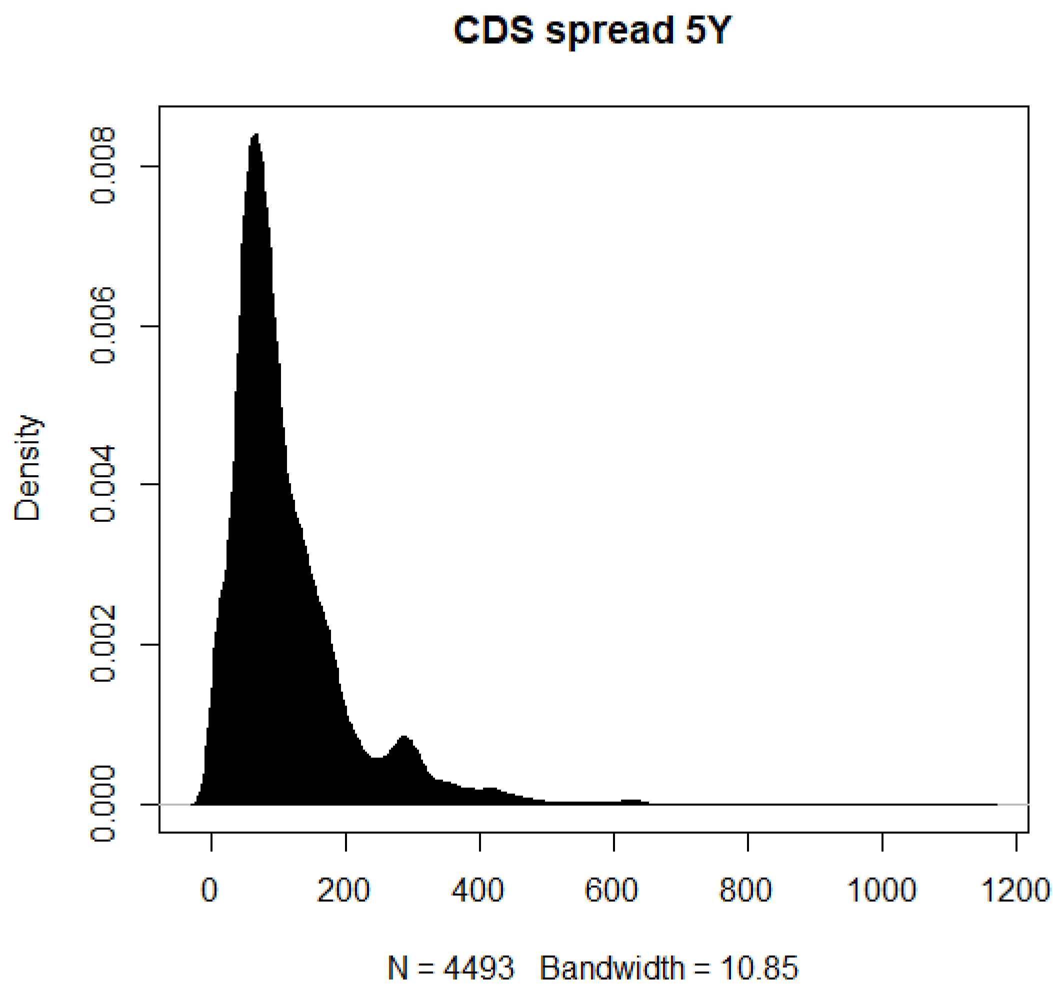


**Figure 4.** Distribution of CDS spreads.

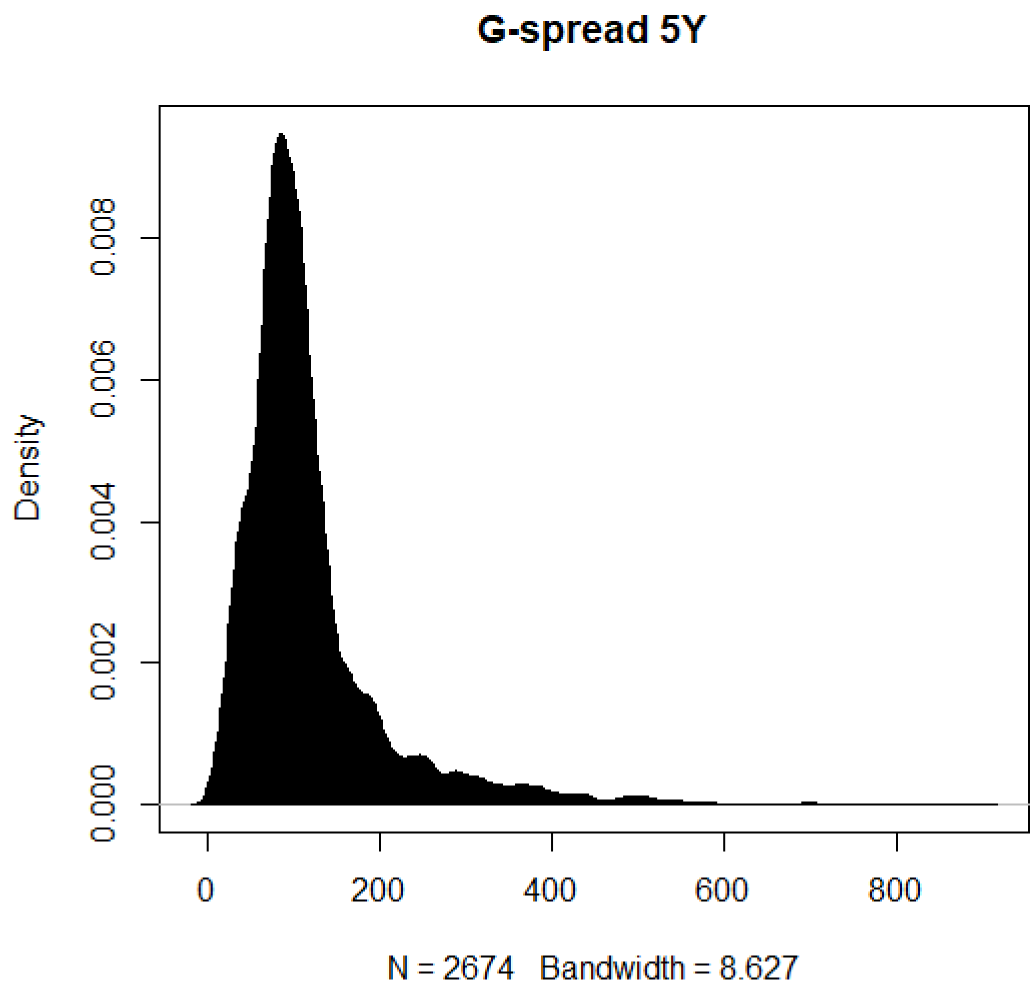


**Figure 5.** Distribution of G-spreads.

CDS spreads are collected for five-year contracts as it is the most liquid tenor on the market (Wang, Wu, Yan & Zhong 2020). To ensure maximal comparison between CDS and bond markets, fixed 5-year points on issuer-specific Bloomberg Valuation curves (BVAL) were chosen for bond spreads. BVAL curves are constructed by Bloomberg from outstanding bonds from the issuer in question and display a complete yield curve with all key tenors, even if the company has not current outstanding debt in all tenor classes, such as in the five-year. Missing real-life maturities and annual points are interpolated from real bonds. This results in a G-spread measure equal to a hypothetical five-year bond held at constant maturity over the whole sample. G-spread used in the data is calculated against a generic benchmark curve in that currency, meaning that the risk-free components in one currency are all equal, eliminating differences in benchmark bonds' credit risk.

A fixed maturity was used for bond spreads as changes in the shape of a credit spread curve are not uncommon and bonds have been found to encounter a pull-to-par effect, where return volatilities decrease as the bond approaches maturity (Beleza, Esquivel, Gaspar & Real 2014). Beleza et. al (2014) do not distinguish between the credit spread component and the benchmark rate, but changing debt maturity along the time-series can potentially distort the value of the credit premium making it less comparable to a CDS contract with fixed tenor. CDS contracts are not directly linked to a single underlying debt instrument, but rather to a basket of eligible deliverable obligations, and the tenors of CDS contracts are fixed (Culp et. al 2016).

Debt class for the BVAL bond curves is senior unsecured with an exception for two German banks in the sample, whose debt is ranked senior subordinated. This is due to a change regarding Germany's resolution act, as since 21 July 2018 German banks have been able to issue senior preferred debt and by a change in legislation, all of the senior bond issued prior to this were subordinated to senior non-preferred. This resulted in disjointed time series of the senior preferred BVAL curves. Due to regressing rating events on *changes* in log spread, this deviation in debt seniority should not pose a problem, as relative changes in credit spreads should be constant, ceteris paribus. CDS prices for both seniorities for these two banks can be assumed to be heavily correlated, implying that the relative changes in different underlying debt classes are somewhat similar in size.

## 4.2. Credit ratings

Credit ratings, rating outlooks and rating watches are collected from Standard and Poor's for a time period corresponding the CDS and bond samples. The particular rating used is the long-term local currency issuer credit rating. First, Standard and Poor's rating classes are converted to numerical values with number 1 corresponding to a 'AAA'-rating. After every end-of month rating in the sample has been assigned a numerical value, rating outlooks are considered (can be positive, negative or stable). Rating watches, which can be negative or positive, are treated analogously to the outlooks. Outlooks and watches affect the rating value by either +0.5 (positive outlook) or -0.5 (negative outlook) and after accounting for these, adjusted rating values are obtained. Average rating value in the CDS sample is 5.97 and 6.69 in the bond sample. When rounded to full rating classes ignoring outlooks, these correspond to classes of 'A' and 'A-', respectively.

The dependent variable in this study's logistic regressions is a binary variable with a value of 1 or 0, depending on whether the adjusted rating value of bank *x* at the end of month *y* has changed from *y - 1 month.* If that is the case, one can determine that there has been a rating event in month *y.* Eventually, this results in binomially distributed dependent variables for every month in the sample. Table 2 shows the amount of rating events per year in the respective spread samples (note that the bond data starts from 2011).

**Table 2.** Rating events per year.

| | Rating events in CDS sample | | Rating events in Bond sample | |
|---|---|---|---|---|
| *Year* | Negative event | Positive event | Negative event | Positive event |
| *2006* | 0 | 1 | n/a | n/a |
| *2007* | 8 | 9 | n/a | n/a |
| *2008* | 34 | 1 | n/a | n/a |
| *2009* | 20 | 4 | n/a | n/a |
| *2010* | 5 | 2 | n/a | n/a |
| *2011* | 26 | 2 | 21 | 0 |
| *2012* | 15 | 3 | 10 | 2 |
| *2013* | 12 | 3 | 12 | 2 |
| *2014* | 9 | 2 | 8 | 2 |
| *2015* | 17 | 11 | 15 | 8 |
| *2016* | 9 | 8 | 6 | 8 |
| *2017* | 3 | 11 | 2 | 8 |
| *2018* | 4 | 7 | 5 | 7 |
| *2019* | 3 | 3 | 4 | 4 |
| *2020* | 8 | 0 | 10 | 0 |
| *Total* | 173 | 67 | 93 | 41 |

## 4.3. Descriptive statistics

Below Tables 3 and 4 display descriptive statistics for the spread data. For most of the sample banks, there is full data for the whole sample period. Banks are not necessarily in the same order in both tables, though all of the banks represented in Table 4 are also present in Table 3. Within the sample banks, there is no significant disparity in bank specific means or standard deviation when reviewed as a group. This reflects the fact that all of banks are investment grade rated operating in developed markets and can be assumed to be of fairly good credit quality, especially if the whole global bank universe is considered.

**Table 3.** Descriptive statistics of CDS spreads per entity.

This table presents descriptive statistics for monthly log CDS spreads and their monthly changes (Δ).

| | **Δ in log spread** | | | | **CDS spread (log)** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Bank** | **Mean** | **SD** | **Skewness** | **Kurtosis** | **Mean** | **SD** | **Skewness** | **Kurtosis** | **N** |
| *1* | 0.01 | 0.24 | 1.11 | 4.78 | 4.14 | 0.80 | 1.00 | 1.80 | 168 |
| *2* | 0.03 | 0.24 | 0.46 | 1.66 | 5.02 | 0.78 | -1.50 | 2.41 | 123 |
| *3* | 0.02 | 0.24 | 1.26 | 7.31 | 5.33 | 0.82 | -1.43 | 2.89 | 147 |
| *4* | 0.04 | 0.23 | 2.05 | 7.77 | 4.35 | 1.14 | -1.32 | 0.98 | 85 |
| *5* | 0.01 | 0.23 | 1.40 | 5.02 | 4.30 | 0.86 | -0.88 | 1.32 | 168 |
| *6* | 0.02 | 0.22 | 0.79 | 3.19 | 3.95 | 0.85 | -1.77 | 3.30 | 147 |
| *7* | 0.01 | 0.22 | 0.76 | 2.41 | 4.59 | 0.87 | -0.77 | 1.08 | 168 |
| *8* | 0.01 | 0.23 | 1.11 | 3.59 | 4.82 | 0.83 | -1.13 | 2.29 | 168 |
| *9* | 0.01 | 0.19 | 0.66 | 3.12 | 4.18 | 0.51 | -0.78 | 1.32 | 168 |
| *10* | 0.01 | 0.23 | 1.55 | 11.34 | 4.69 | 0.71 | 0.32 | 0.12 | 168 |
| *11* | 0.01 | 0.21 | 1.24 | 4.34 | 4.62 | 0.58 | -0.06 | 0.66 | 168 |
| *12* | 0.01 | 0.22 | 1.69 | 7.11 | 4.43 | 0.82 | -0.20 | 0.37 | 168 |
| *13* | 0.01 | 0.24 | 0.76 | 3.66 | 4.08 | 0.85 | -0.87 | 1.06 | 168 |
| *14* | 0.01 | 0.23 | 0.84 | 3.46 | 4.36 | 0.76 | -1.66 | 3.76 | 168 |
| *15* | 0.01 | 0.21 | 0.65 | 1.57 | 4.36 | 0.60 | -1.51 | 3.29 | 168 |
| *16* | 0.01 | 0.22 | 0.91 | 4.64 | 4.06 | 0.76 | -1.58 | 2.50 | 145 |
| *17* | 0.02 | 0.25 | 0.82 | 5.40 | 4.54 | 0.88 | -1.68 | 3.75 | 168 |
| *18* | 0.01 | 0.21 | 0.39 | 1.33 | 4.41 | 0.76 | -0.55 | 1.10 | 168 |
| *19* | 0.01 | 0.21 | 0.47 | 2.14 | 4.33 | 0.89 | -1.09 | 1.28 | 143 |
| *20* | 0.01 | 0.24 | 1.67 | 10.57 | 4.07 | 0.66 | -1.67 | 3.72 | 164 |
| *21* | 0.01 | 0.23 | 0.94 | 6.90 | 4.16 | 0.89 | -1.24 | 1.63 | 147 |
| *22* | 0.02 | 0.24 | 1.13 | 8.42 | 4.39 | 1.00 | -1.29 | 1.86 | 138 |
| *23* | 0.01 | 0.21 | 1.51 | 6.44 | 4.47 | 0.81 | -0.41 | 0.33 | 155 |
| *24* | -0.00 | 0.18 | -0.04 | 0.63 | 4.57 | 0.45 | -0.23 | 0.16 | 123 |
| *25* | 0.01 | 0.21 | 0.84 | 3.02 | 4.50 | 0.80 | -0.72 | 1.57 | 168 |
| *26* | 0.01 | 0.21 | 0.80 | 4.45 | 4.10 | 0.63 | -1.20 | 3.08 | 168 |
| *27* | 0.01 | 0.24 | 1.61 | 9.75 | 4.10 | 0.66 | -1.57 | 3.47 | 165 |
| *28* | 0.02 | 0.17 | 2.77 | 13.32 | 5.40 | 0.75 | -1.24 | 4.56 | 123 |
| *29* | 0.01 | 0.23 | 0.66 | 1.71 | 4.65 | 0.90 | -1.18 | 2.29 | 168 |

*Not necessarily in the same order than in Table 4

**Table 4.** Descriptive statistics of G-spreads per entity.

This table presents descriptive statistics for monthly log G-spreads and their monthly changes (Δ).

| | Δ in log spread | | | | G spread (log) | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Bank*** | **Mean** | **SD** | **Skewness** | **Kurtosis** | **Mean** | **SD** | **Skewness** | **Kurtosis** | **N** |
| *1* | 0.01 | 0.17 | 0.78 | 5.65 | 4.65 | 0.40 | 1.02 | 0.89 | 114 |
| *2* | -0.00 | 0.17 | 0.76 | 2.71 | 4.54 | 0.38 | 1.06 | 0.82 | 114 |
| *3* | -0.00 | 0.17 | 1.34 | 5.07 | 4.79 | 0.43 | 1.31 | 1.16 | 114 |
| *4* | -0.01 | 0.15 | 0.74 | 0.83 | 4.77 | 0.39 | 0.89 | 0.33 | 90 |
| *5* | -0.01 | 0.14 | 1.88 | 9.79 | 4.90 | 0.41 | 1.02 | 0.42 | 114 |
| *6* | -0.00 | 0.16 | 1.47 | 6.74 | 4.57 | 0.36 | 1.13 | 0.91 | 114 |
| *7* | -0.00 | 0.09 | 2.51 | 16.15 | 3.84 | 0.39 | 1.11 | 0.38 | 114 |
| *8* | -0.00 | 0.16 | 0.93 | 3.82 | 4.64 | 0.49 | 0.91 | 0.22 | 114 |
| *9* | 0.01 | 0.15 | 0.83 | 2.26 | 4.77 | 0.42 | -0.08 | -1.04 | 94 |
| *10* | -0.00 | 0.16 | 1.32 | 4.95 | 4.93 | 0.44 | 1.29 | 1.01 | 114 |
| *11* | -0.01 | 0.16 | 1.79 | 9.23 | 4.55 | 0.43 | 0.87 | -0.02 | 114 |
| *12* | -0.00 | 0.19 | 1.40 | 3.91 | 5.20 | 0.51 | 0.58 | -0.52 | 114 |
| *13* | -0.00 | 0.18 | 1.39 | 5.39 | 4.59 | 0.31 | 1.25 | 1.61 | 114 |
| *14* | -0.01 | 0.16 | 0.67 | 2.22 | 4.70 | 0.50 | 1.25 | 1.01 | 114 |
| *15* | -0.01 | 0.19 | 1.54 | 7.02 | 4.72 | 0.56 | 1.10 | 0.94 | 114 |
| *16* | -0.01 | 0.17 | 1.23 | 4.66 | 4.95 | 0.50 | 1.34 | 0.97 | 114 |
| *17* | -0.00 | 0.20 | 1.38 | 6.05 | 4.97 | 0.48 | 0.86 | 0.38 | 114 |
| *18* | 0.00 | 0.11 | 2.19 | 12.19 | 3.72 | 0.41 | 0.99 | 0.02 | 114 |
| *19* | -0.01 | 0.15 | 1.48 | 10.02 | 4.41 | 0.36 | 0.86 | 0.27 | 114 |
| *20* | -0.00 | 0.18 | 0.88 | 2.55 | 4.60 | 0.47 | 1.18 | 1.00 | 114 |
| *21* | 0.01 | 0.14 | -0.26 | 0.92 | 2.96 | 0.48 | -0.39 | -1.22 | 96 |
| *22* | -0.00 | 0.13 | -0.03 | 0.72 | 3.99 | 0.35 | 0.88 | 0.58 | 114 |
| *23* | -0.00 | 0.21 | 1.65 | 5.24 | 5.20 | 0.52 | 0.49 | 0.16 | 114 |
| *24* | -0.00 | 0.17 | 1.60 | 8.40 | 4.43 | 0.32 | 0.64 | 0.44 | 114 |

*Not necessarily in the same order than in Table 3

Tables 5 and 6 report descriptive statistics of CDS spreads and G-spreads as whole separate groups. By comparing the log spread values from these two tables, we can see that the main statistical properties of both spreads are quite similar, which is expected as the sample banks are mostly the same in both groups (six banks included exclusively in the CDS data). The two different spread samples indicate somewhat mutual levels of risk premium between CDS and bond markets. By transforming the log spreads back to their original values, the median CDS spread in the sample is 86.49 bps while the median G-spread is 96.54 bps. The middle 50 % percent (the mass between the 25$^{th}$ and 75$^{th}$ percentile) is located between 55.70 and 142.59 bps for CDS spreads and 70.11 and 132.95 bps for G-spreads. Though very similar, CDS data seems to carry more extreme values, which is also confirmed by higher kurtosis compared to G-spreads.

**Table 5.** Descriptive statistics of CDS spreads for the whole sample group.

This table presents aggregate descriptive statistics for CDS spreads.

| | **Δ in log spread** | **CDS spread (log)** |
|---|---|---|
| *N* | 4464* | 4493 |
| *Min* | -1.03 | 1.17 |
| *1Q* | -0.11 | 4.02 |
| *Median* | -0.01 | 4.46 |
| *3Q* | 0.11 | 4.96 |
| *Max* | 1.50 | 7.04 |
| *Mean* | 0.01 | 4.43 |
| *SD* | 0.22 | 0.85 |
| *Skewness* | 1.08 | -0.79 |
| *Kurtosis* | 5.62 | 1.82 |

*N for Δ in log spread for individual regressions depends on the monthly lag used as every additional lag decreases N by 29 (N for banks in the sample). Regressions carried a minimum lag of -1 resulting in a maximum N of 4435.

**Table 6.** Descriptive statistics of G-spreads for the whole sample group.

This table presents aggregate descriptive statistics for G-spreads.

| | **Δ in log spread** | **G-spread (log)** |
|---|---|---|
| *N* | 2650* | 2674 |
| *Min* | -0.53 | 1.96 |
| *1Q* | -0.09 | 4.25 |
| *Median* | -0.01 | 4.57 |
| *3Q* | 0.06 | 4.89 |
| *Max* | 1.06 | 6.79 |
| *Mean* | -0.00 | 4.56 |
| *SD* | 0.16 | 0.64 |
| *Skewness* | 1.30 | -0.24 |
| *Kurtosis* | 6.14 | 1.39 |

*N for Δ in log spread for individual regressions depends on the monthly lag used as every additional lag decreases N by 24 (N for banks in the sample). Regressions carried a minimum lag of -1 resulting in a maximum N of 2626.

## 5. METHODOLOGY

To determine the exact methodology, previous studies on the subject were examined for reference. Various different models has been applied for the investigation of the predictive power of spreads, and this thesis ended up using a similar model to Rodríguez et al. (2019). The predictive power is investigated with a basic logistic regression where the dependent variable, rating event, is binary variable and the independent variable is the monthly change in log spread lagged back *m* months. Basic logistic regression models whether a change in independent variable(s) increases the probability of success for the dependent variable. That is, the model measures whether the lagged monthly changes in spreads have any effect on the probability of a rating event in month *t.*

The regression model used can simply be expressed as:

(5) $$logit[P(1)] = a + \Delta s_{i,t-m}$$

where:

$logit[P(1)]$ = probability of success, i.e., that the rating event variable has a value of 1,

$a$ = constant,

$\Delta s_{i,t-m}$ = one month spread change for bank *i* at time *t*, lagged back *m* months.

To control for contamination, when a rating event is immediately following another rating event in the previous month, the succeeding one is removed from the sample. No control variables are added to the model as they would most likely be highly correlated with spread levels and would distort the results for the predictive power of spreads. Both ratings and spreads are measures of aggregate risk, viewed by different parties, and by adding controls the model would actually, inadvertently, attempt to find the fundamental drivers of ratings rather than determining whether the market prices credit risk systematically prior to changes in ratings. As spreads are measures of overall credit quality, the purpose of this thesis is to find out how well they reflect credit fundamentals for banks compared to ratings.

## 5.1. Robustness tests

Despite using spread changes as the independent variable, the data is checked for stationarity to ensure robust results from the model. To make sure that statistical properties of spreads do not vary over time, two unit root tests designed for panel data are performed. The first test is the cross-sectionally augmented Im, Pesaran and Shin test (CIPS) introduced by Pesaran (2007), which improves the first generation IPS test (Im, Pesaran & Shin 2003) by accounting for cross-sectional dependence. The second test is the Choi (2002) inverse normal combination test, which similarly to the CIPS test does not assume cross-sectional independence like the original version of the test (Choi 2001).

Unit root is tested on log spread values to demonstrate that also level values could be used credibly in the model. Test results for spread changes are not reported, as the test statistic reject the null hypothesis of a unit root with remarkable confidence levels. Second generation unit root tests are applied as Pesaran (2007) argues that in the presence of high cross-sectional dependence, first generations tests seem to over-reject the null hypothesis by a substantial amount. Even though the sample in this study is not considerably small, Pesaran (2007) demonstrates that especially CIPS and the Choi test used in this paper perform strongly even for small sample sizes with a high degree of cross-sectional dependence and some residual autocorrelation.

CIPS test is based on the cross-sectionally Augmented Dickey Fuller (CADF) statistic (Pesaran 2007, see also Hansen 1995), more precisely on the *t* ratio of estimate *b* in the following OLS CADF regression:

(6) $$\Delta y_{it} = a_i + b_i y_{it-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it}$$

where:

$y_{it}$ = log spread of bank *i* in month *t*,

$\bar{y}_t$ = cross-sectional mean of log spreads in month *t*.

$H_0$ of a unit root is given as $b_i = 0$ for all *i* against the alternative hypothesis $H_1$: *b* < 0. The result is determined by the actual CIPS statistic, which is an average of the individual CADF statistics:

(7) $$CIPS(N,T) = N^{-1} \sum_{i=1}^{N} t_i(N,T)$$

where:

$N$ = cross-section dimension,

$T$ = time series dimension,

$t_i$ = CADF statistic for bank *i.*

The distribution for CIPS is not standard and critical values depend on both *N* and *T.* Choi's (2002) cross-sectionally augmented inverse normal test is similarly based on the CADF statistic and it combines the p-values of the individual Dickey-Fuller tests for the following test statistic *z*:

(7) $$Z(N,T) = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1} (p_{iT})$$

where:

$N$ = cross-section dimension,

$T$ = time series dimension,

$\Phi$ = standard normal cumulative distribution function,

$p_{iT}$ = *p*-value of the unit root test for the individual cross-section unit *i*.

Results from both tests confirm stationarity for log spread values and their changes. These are reported in Tables 7 and 8.

**Table 7.** Unit root tests for CDS spreads.

This table presents the results of two panel unit root tests run on the sample of CDS spreads. Test employed are the cross-sectionally augmented Im, Pesaran and Shin test (CIPS) (Pesaran 2007) and the cross-sectionally augmented Choi's inverse normal combination test (Choi Inv.) (Choi 2002).

| | **CDS spread (log)** | | | |
|---|---|---|---|---|
| | **CIPS** | | **Choi Inv.** | |
| ***Nb of lags*** | ***t-stat.*** | ***p-value*** | ***t-stat.*** | ***p-value*** |
| 1 | -2.701 | <.01*** | -11.153 | <.01*** |
| 2 | -2.654 | <.01*** | -11.603 | <.01*** |
| 3 | -2.605 | <.01*** | -12.180 | <.01*** |
| 4 | -2.633 | <.01*** | -11.669 | <.01*** |

Choi's inverse normal test statistic is based on the normal distribution. CIPS critival values depend on the test setting (see Pesaran 2007).

**Table 8.** Unit root tests for G-spreads.

This table presents the results of two panel unit root tests run on the sample of G-spreads. Test employed are the cross-sectionally augmented Im, Pesaran and Shin test (CIPS) (Pesaran 2007) and the cross-sectionally augmented Choi's inverse normal combination test (Choi Inv.) (Choi 2002).

| | **G-spread (log)** | | | |
|---|---|---|---|---|
| | **CIPS** | | **Choi Inv.** | |
| ***Nb of lags*** | ***t-stat.*** | ***p-value*** | ***t-stat.*** | ***p-value*** |
| 1 | -2.997 | <.001*** | -3.001 | 0.001*** |
| 2 | -2.588 | <.001*** | -2.168 | 0.015** |
| 3 | -2.437 | <.001*** | -3.549 | <.001*** |
| 4 | -2.331 | 0.012** | -3.539 | <.001*** |

Choi's inverse normal test statistic is based on the normal distribution. CIPS critival values depend on the test setting (see Pesaran 2007).

To test the goodness of fit of the logistic regression model, the Hosmer-Lemeshow test is applied (Hosmer & Lemeshow 1980). P-values for this test are reported in the regression tables in chapter 6. Null hypothesis for the Hosmer-Lemeshow test is that the model is adequately specified, i.e., the observed outcomes and the outcomes expected by the model do not differ significantly. Results of these tests indicate that the logistic regression model used is a reasonable fit, as seen in Tables 9-17.

# 6. RESULTS

This chapter covers the main empirical findings of this thesis and reports the results from logistic regressions. Predictive power of spreads were examined in relation to any movements in ratings as well as for positive and negative events alone. Overall, the information value from G-spreads and CDS spreads seem to be fairly identical and no clear leader of price discovery is found. However, both markets are proven to systematically price in upcoming rating changes, leaning in favor of incorporating market-based risk measures in credit analysis, even if the only interest is to predict future development of ratings. This is an important feature in it itself, as many portfolio managers might mostly ignore default risk if the issuer is rated high enough, meaning that for example, a downgrade from AA+ to AA would not raise major concerns about a possible default but would rather have other more technical implications regarding exposure allocation etc. In addition, spreads continue rising after a negative rating event as Rodríguez et. al (2019) demonstrate, meaning that realized rating events affect investment returns at least in the short-term.

## 6.1. Credit default swaps

As discussed in the previous chapter, CDS spreads are studied in two sample periods, one covering the whole collected data period from October 2006 to September 2020 and the other starting from 2010. That is, the other sample excludes the turbulence peak of the recent financial crisis. First, the longer sample is reviewed.

### 6.1.1. Sample period: 2006-2020

Table 9 reports the results when both positive and negative ratings events are examined alike with no distinction between them. *ΔCDS* denotes the dependent variable in the model, which is a one-month change in log spread lagged back *m* months. Number of rating events in every subsample is shown in every table and is denoted by *Event N*. *Hosmer-Lemeshow* is the p-value from the respective test for the model's goodness of fit.

**Table 9.** CDS spreads and all rating events in 2006-2020.

This table presents coefficients from logistic regressions, where all rating events (positive/negative) are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| Δ Rating value \| Independent variable: CDS \| Period: 2006-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *ΔCDS* | 1.050*** | -0.189 | 1.093*** | 0.422 | -0.030 | 0.971*** | 0.119 | -0.450 | 0.095 |
| | (0.261) | (0.306) | (0.260) | (0.286) | (0.302) | (0.266) | (0.301) | (0.319) | (0.305) |
| | [<.001] | [0.537] | [<.001] | [0.140] | [0.922] | [<.001] | [0.693] | [0.159] | [0.756] |
| *Intercept* | -2.900*** | -2.861*** | -2.899*** | -2.871*** | -2.860*** | -2.890*** | -2.847*** | -2.846*** | -2.860*** |
| | (0.069) | (0.067) | (0.069) | (0.068) | (0.067) | (0.069) | (0.067) | (0.068) | (0.068) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *ΔCDS N* | 4435 | 4406 | 4377 | 4348 | 4319 | 4290 | 4261 | 4232 | 4203 |
| *Event N* | 240 | 238 | 238 | 235 | 234 | 234 | 234 | 232 | 228 |
| *Hosmer-Lemeshow* | [0.024] | [0.008] | [0.086] | [0.202] | [0.915] | [0.147] | [0.463] | [0.108] | [0.926] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

Coefficients reveal mixed results regarding the anticipation of a rating change in the credit derivative market. One month change in spread from the previous month (i.e., with a one-month lag) seems to be statistically highly significant, accompanied with changes lagged three and six months. Hence there seems to be no consistent and continuous change in spread levels prior to a change in rating or outlook. Coefficients are mostly positive, suggesting that the results are driven by increases in spread levels. This leads to an assumption that there is a greater impact to be found in negative rating events, which is consistent with the findings by Hull et. al (2004).

Tables 10 and 11 report results individually for negative and positive events. One can see that spreads predict negative rating events much more systematically. During 2006-2020 the only statistically significant coefficient regards to positive rating events is the five-month lag. One could try to argue that when positive information appears on the market, rating or its outlook changes on average five months later. Still, it is very hard to draw strong conclusions from the results.

**Table 10.** CDS spreads and positive rating events in 2006-2020.

This table presents coefficients from logistic regressions, where positive rating events are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| +Δ Rating value \| Independent variable: CDS \| Period: 2006-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *ΔCDS* | 0.123 | -0.043 | -0.657 | -0.521 | -1.632*** | 0.427 | -0.269 | -0.430 | 0.202 |
| | (0.547) | (0.587) | (0.594) | (0.597) | (0.614) | (0.540) | (0.595) | (0.614) | (0.583) |
| | [0.822] | [0.467] | [0.269] | [0.383] | [0.008] | [0.430] | [0.650] | [0.483] | [0.728] |
| *Intercept* | -4.179*** | -4.200*** | -4.196*** | -4.219*** | -4.266*** | -4.233*** | -4.214*** | -4.241*** | -4.273*** |
| | (0.124) | (0.125) | (0.125) | (0.127) | (0.133) | (0.130) | (0.128) | (0.130) | (0.133) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *ΔCDS N* | 4435 | 4406 | 4377 | 4348 | 4319 | 4290 | 4261 | 4232 | 4203 |
| *Event N* | 67 | 65 | 65 | 63 | 62 | 62 | 62 | 60 | 58 |
| *Hosmer-Lemeshow* | [0.597] | [0.140] | [0.422] | [0.700] | [0.369] | [0.306] | [0.029] | [0.333] | [0.105] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

**Table 11.** CDS spreads and negative rating events in 2006-2020.

This table presents coefficients from logistic regressions, where negative rating events are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| –Δ Rating value \| Independent variable: CDS \| Period: 2006-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *ΔCDS* | 1.318*** | -0.095 | 1.551*** | 0.713** | 0.048 | 1.117*** | 0.0251 | -0.443 | 0.053 |
| | (0.289) | (0.353) | (0.279) | (0.317) | (0.328) | (0.297) | (0.342) | (0.368) | (0.352) |
| | [<.001] | [0.789] | [<.001] | [0.025] | [0.147] | [<.001] | [0.464] | [0.228] | [0.879] |
| *Intercept* | -3.264*** | -3.196*** | -3.272*** | -3.211*** | -3.195*** | -3.223*** | -3.173*** | -3.161*** | -3.167*** |
| | (0.081) | (0.078) | (0.082) | (0.079) | (0.079) | (0.081) | (0.078) | (0.078) | (0.078) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *ΔCDS N* | 4435 | 4406 | 4377 | 4348 | 4319 | 4290 | 4261 | 4232 | 4203 |
| *Event N* | 173 | 173 | 173 | 172 | 172 | 172 | 172 | 172 | 170 |
| *Hosmer-Lemeshow* | [0.005] | [0.009] | [0.040] | [0.109] | [0.595] | [0.003] | [0.923] | [0.076] | [0.838] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

Prior to negative ratings, there seems to be some price discovery occurring in the CDS markets, as we concluded above from Table 9. In Table 11, we can see that lagged spread changes are significant with the following lags: one, three, four and six months. These results show more promise than the ones combining both positive and negative ratings events, but there is some inconsistency in the pattern. At least one cannot conclude that spreads react "linearly" before an event, as the coefficients for two- and four-month lags are nonsignificant. It is possible that after the initial negative information is revealed, the markets balance their view about the value of the asset and random movements in the spread occur in both directions, as sentiment drives the spread. Rarely it is so that during every month prior a rating event new information is revealed, which would make the changes in spread more linear, when the preceding months are observed as one time-series.

These differences in the amount of lag months displaying significance between negative and positive events are logical, when one thinks about the general nature of positive and negative information and especially the way market prices this information. Sudden negative events are more common than sudden positive events and this is why most asset returns are negatively skewed carrying tail risk. Overall, positive or neutral sentiment seems to be a steadier state of moderate positive returns (and decreases or no large negative movements in spread) lasting usually relatively long, as significant negative events, both idiosyncratic and systematic, seem to be more extreme and sudden. In the case of this study, this can be seen in the distribution of spread values presented in chapter 5 (it should be noted that as spreads and returns are negatively correlated, most negative values creditwise are the highest spread values in the right tail).

### 6.1.2. Sample period: 2010-2020

As the 2008 financial crisis is unique in many ways and the sudden unraveling of events took the market by surprise to some extent, it is reasonable to investigate the predictive power of spreads without this crisis period. This is justified because years 2008 and 2009 may have an undesirable effect on the results regarding longer lags in our study, as rating agencies changed most ratings within 9 months, which is the maximum lag studied, after the crisis started. In addition, it is easy to argue that the financial markets changed permanently after the crisis. Especially since the rating agencies were much criticized, the crisis in 2008 lead to a paradigm change in fundamentals of risk management and to how credit and liquidity risks are viewed by market participants.

Table 12 reports the results for the shorter sample period regarding all rating events. With the exception of the four-month lag, all of the coefficients are significant at 10 % level from one to six months. Spread change one month prior to an event has a higher p-value for the shorter sample indicating a bit less robust results, which is possibly due to the fact that in overall rating changes were priced earlier relative to the rating announcement, when the crisis period of 2008 and 2009 was excluded from the sample. Contrary to Rodríguez et al. (2019), no predictive power is observed in CDS spreads beyond 6 months.

**Table 12.** CDS spreads and all rating events in 2010-2020.

This table presents coefficients from logistic regressions, where all rating events (positive/negative) are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| Δ Rating value \| Independent variable: CDS \| Period: 2010-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *ΔCDS* | 0.849* | 0.901* | 1.553*** | -0.447 | 0.800* | 1.114** | -0.598 | -0.020 | 0.0053 |
| | (0.476) | (0.476) | (0.454) | (0.505) | (0.470) | (0.464) | (0.523) | (0.517) | (0.514) |
| | [0.075] | [0.058] | [<.001] | [0.377] | [0.089] | [0.016] | [0.252] | [0.969] | [0.918] |
| *Intercept* | -2.954*** | -2.956*** | -2.976*** | -2.956*** | -2.957*** | -2.966*** | -2.960*** | -2.953*** | -2.952*** |
| | (0.082) | (0.082) | (0.083) | (0.082) | (0.082) | (0.083) | (0.082) | (0.082) | (0.082) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *ΔCDS N* | 3185 | 3156 | 3127 | 3098 | 3069 | 3040 | 3011 | 2982 | 2953 |
| *Event N* | 158 | 158 | 158 | 158 | 158 | 158 | 158 | 158 | 158 |
| *Hosmer-Lemeshow* | [0.002] | [0.332] | [0.115] | [0.091] | [0.472] | [0.270] | [0.185] | [0.003] | [0.170] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

Tables 13 and 14 report results individually for positive and negative events. Regarding rating and outlook upgrades, spreads seem to react 4-6 months prior to the change, as all of those three coefficients are significant at 5 % level. Again, no continuous pattern is observed leading up to the event month. When positive events are excluded, the results are more robust. Except the nonsignificant four-month lag, monthly spread increases one to five months before time *t* are increasing the probability of a rating event in month *t*. Coefficients for spread changes with positive events are negative and vice versa for negative events, as expected.

Overall, results from the shorter sample are indicating stronger predictive power in CDS spreads and a relationship between spreads and rating changes is clearly observed. The relationship is stronger for negative ratings events, which demonstrate a somewhat consistent increase in CDS spreads for the preceding months. As for positive events, it is more difficult to draw a clear conclusion as the only significant coefficients were with lags of 4-6 months. Moreover, the coefficient for the six-month lag is positive, which is intuitively of the wrong sign and cast uncertainty on the results regarding positive rating events.

**Table 13.** CDS spreads and positive rating events in 2010-2020.

This table presents coefficients from logistic regressions, where positive rating events are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| +Δ Rating value \| Independent variable: CDS \| Period: 2010-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *ΔCDS* | -0.218 | -0.068 | -0.222 | -1.923** | -2.424*** | 1.533** | -0.594 | -1.271 | 1.295 |
| | (0.878) | (0.890) | (0.872) | (0.922) | (0.923) | (0.768) | (0.905) | (0.9312) | (0.837) |
| | [0.804] | [0.453] | [0.799] | [0.037] | [0.009] | [0.046] | [0.511] | [0.172] | [0.122] |
| *Intercept* | -4.121*** | -4.129*** | -4.120*** | -4.169*** | -4.201*** | -4.148*** | -4.125*** | -4.146*** | -4.132*** |
| | (0.142) | (0.143) | (0.142) | (0.148) | (0.153) | (0.145) | (0.142) | (0.145) | (0.143) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *ΔCDS N* | 3185 | 3156 | 3127 | 3098 | 3069 | 3040 | 3011 | 2982 | 2953 |
| *Event N* | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 |
| *Hosmer-Lemeshow* | [0.272] | [0.912] | [0.221] | [0.957] | [0.778] | [0.681] | [0.025] | [0.541] | [0.336] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

**Table 14.** CDS spreads and negative rating events in 2010-2020.

This table presents coefficients from logistic regressions, where negative rating events are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| –Δ Rating value \| Independent variable: CDS \| Period: 2010-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *ΔCDS* | 1.288** | 1.535*** | 2.226*** | 0.220 | 2.003*** | 0.855 | -0.581 | 0.549 | -0.603 |
| | (0.554) | (0.055) | (0.517) | (0.588) | (0.520) | (0.566) | (0.630) | (0.609) | (0.634) |
| | [0.020] | [0.005] | [<.001] | [0.708] | [<.001] | [0.131] | [0.356] | [0.368] | [0.342] |
| *Intercept* | -3.370*** | -3.379*** | -3.416*** | -3.360*** | -3.406*** | -3.367*** | -3.366*** | -3.359*** | -3.367*** |
| | (0.099) | (0.100) | (0.103) | (0.098) | (0.102) | (0.099) | (0.099) | (0.098) | (0.099) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *ΔCDS N* | 3185 | 3156 | 3127 | 3098 | 3069 | 3040 | 3011 | 2982 | 2953 |
| *Event N* | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 | 107 |
| *Hosmer-Lemeshow* | [<.001] | [0.035] | [0.371] | [0.072] | [0.392] | [0.148] | [0.759] | [0.001] | [0.099] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

## 6.2. Bonds

G-spread data for was available for 2011-2020, making the bond sample comparable to the shorter CDS sample. Overall, the results from bond spreads were quite similar to those from CDS prices. Pearson correlation coefficient for CDS spreads and G-spreads in the data sample was 0.73, showing that the spread measures from two different markets are fairly highly correlated, but not in an extreme way. For G-spreads, no clear pattern was found regarding positive rating events and negative ratings seemed to drive the overall sample, as was the case with CDS spreads. Tables 15, 16 and 17 report the results from the bond spread sample.

**Table 15.** G-spreads and all rating events in 2011-2020.

This table presents coefficients from logistic regressions, where all rating events (positive/negative) are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| Δ Rating value \| Independent variable: Bond \| Period: 2011-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *Δ G-spread* | 1.529*** | 0.746 | 1.361*** | -0.689 | 1.250*** | 1.495*** | -0.410 | 0.033 | -0.445 |
| | (0.459) | (0.502) | (0.469) | (0.578) | (0.048) | (0.472) | (0.675) | (0.679) | (0.689) |
| | [<.001] | [0.138] | [0.004] | [0.234] | [0.009] | [0.002] | [0.544] | [0.962] | [0.518] |
| *Intercept* | -2.949*** | -2.919*** | -2.934*** | -2.907*** | -2.938*** | -2.949*** | -3.018*** | -3.033*** | -3.026*** |
| | (0.091) | (0.089) | (0.091) | (0.089) | (0.092) | (0.093) | (0.095) | (0.096) | (0.0967) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *Δ G-spread N* | 2626 | 2602 | 2578 | 2554 | 2530 | 2506 | 2482 | 2458 | 2434 |
| *Event N* | 134 | 134 | 133 | 133 | 130 | 129 | 116 | 113 | 113 |
| *Hosmer-Lemeshow* | [0.437] | [0.351] | [0.083] | [0.071] | [0.063] | [0.751] | [0.184] | [0.002] | [0.999] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

As seen from Table 15, monthly spread changes lagged back one, three, five and six months seem to be significant in increasing the probability of a future rating event. Again, similar to CDS spreads, the pattern in spread changes with respect to time is not cohesive, meaning that once the G-spread starts to react for a future event, it does not continue to move similarly every month prior to the event. This makes it harder to predict rating changes with credit spreads, as some of the preceding months show no relation to the event. Estimating the probability of a rating event becomes trickier for an analyst, as he or she must judge after every month if the prior monthly changes still indicate an upcoming event, or if the newest month is signaling a more stable situation creditwise regarding the issuer.

**Table 16.** G-spreads and positive rating events in 2011-2020.

This table presents coefficients from logistic regressions, where positive rating events are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

| +Δ Rating value \| Independent variable: Bond \| Period: 2011-2020 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
| *Δ G-spread* | -0.321 | 0.162 | 0.133 | -3.555*** | -0.356 | 1.505* | -0.227 | 0.547 | 0.869 |
| | (0.997) | (0.949) | (0.952) | (1.091) | (1.000) | (0.789) | (1.112) | (1.084) | (1.062) |
| | [0.747] | [0.864] | [0.889] | [0.001] | [0.722] | [0.057] | [0.838] | [0.614] | [0.413] |
| *Intercept* | -4.146*** | -4.135*** | -4.125*** | -4.253** | -4.107*** | -4.135*** | -4.088*** | -4.078*** | -4.071*** |
| | (0.158) | (0.157) | (0.158) | (0.178) | (0.158) | (0.162) | (0.158) | (0.158) | (0.158) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *Δ G-spread N* | 2626 | 2602 | 2578 | 2554 | 2530 | 2506 | 2482 | 2458 | 2434 |
| *Event N* | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 | 41 |
| *Hosmer-Lemeshow* | [0.466] | [0.761] | [0.164] | [0.341] | [0.630] | [0.303] | [0.051] | [0.050] | [0.952] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

Table 16 shows that G-spreads cannot be comfortably utilized in predicting positive rating events. Monthly change with a four-month lag seems to be highly significant, accompanied only by the six-month lag, which is just barely nonsignificant already at a 5 % confidence level. Strikingly, the coefficient for the six-month lag is positive and not negative as intuitively expected, which was exactly the case with the results from CDS spreads.

However it is interesting that the only significant monthly changes are several months prior to an event, similar to the results from CDS data. From these tests, it is hard to distinguish whether this is due to spreads stabilizing more before the event, compared to negative events, or because negative rating events are announced faster by the rating agencies after a change in credit quality. This poses an interesting question for possible future research.

**Table 17.** G-spreads and negative rating events in 2011-2020.

This table presents coefficients from logistic regressions, where negative rating events are considered a binary success in the dependent variable. Standard errors for the coefficients are reported in parentheses and p-values are reported in brackets. Number of monthly changes in log spread is reported for every model as well as the number of rating events. P-values for the Hosmer-Lemeshow goodness of fit test are also reported.

–Δ Rating value | Independent variable: Bond | Period: 2011-2020

| Lag (months) | -1 | -2 | -3 | -4 | -5 | -6 | -7 | -8 | -9 |
|---|---|---|---|---|---|---|---|---|---|
| *Δ G-spread* | 2.084*** | 0.959* | 1.761*** | 0.406 | 1.780*** | 1.412** | -0.499 | -0.276 | -1.247 |
| | (0.500) | (0.579) | (0.523) | (0.624) | (0.529) | (0.564) | (0.835) | (0.853) | (0.874) |
| | [<.001] | [0.098] | [<.001] | [0.515] | [<.001] | [0.012] | [0.551] | [0.746] | [0.154] |
| *Intercept* | -3.360*** | -3.305*** | -3.338*** | -3.289*** | -3.359*** | -3.346*** | -3.472*** | -3.503*** | -3.501*** |
| | (0.110) | (0.107) | (0.101) | (0.106) | (0.112) | (0.111) | (0.118) | (0.120) | (0.122) |
| | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] | [<.001] |
| *Δ G-spread N* | 2626 | 2602 | 2578 | 2554 | 2530 | 2506 | 2482 | 2458 | 2434 |
| *Event N* | 93 | 93 | 92 | 92 | 89 | 88 | 75 | 72 | 72 |
| *Hosmer-Lemeshow* | [0.138] | [0.342] | [0.106] | [0.047] | [0.060] | [0.958] | [0.846] | [0.065] | [0.942] |

***Significant at 0.01 level.
**Significant at 0.05 level.
*Significant at 0.10 level.

For negative events, all of the lagged spread changes between one and six months prior to an event are significant at 10 % level except the four-month lag. This is again very similar to the results from CDS prices and for no sample tested, lags beyond six months showed significance in results. One can conclude that compared to the Rodríguez et al. (2019) study of sovereign CDS movements, investment-grade financials do not display predictive power in their credit spreads for as long in advance (sovereign CDS spreads reacted up to nine months prior a change in rating or outlook). Overall, similar to CDS markets, G-spreads derived from bond prices begin to react for a future rating event around 4-6 months before the actual rating announcement.

# 7. CONCLUSION

The predictive power of credit spreads of investment grade banks on upcoming changes in ratings or rating outlooks and watches were studied in this thesis with the help of a logistic regression model. A binary variable (1 for a change in rating value, 0 for no change) was regressed on lagged monthly changes in log spreads. CDS spreads were examined both for periods 2006-2020 and 2010-2020. In order to compare the price discovery process between derivative and bond markets, G-spreads were also examined (i.e., yield spread on a government bond).

As the sample banks originated from all over the world, the G-spread used was quoted against a generic combined government curve in the respective currency, eliminating the unambiguous credit risk component in different government bonds. A maximum of 29 banks were studied in order to determine, if and how long prior a rating announcement credit spreads of these banks react to an upcoming rating change. The idea was to demonstrate potentially the superiority of market-based measures as an information source of credit quality, compared to the ratings assigned by credit rating agencies.

It is important to note that different spread measures derived from a single bond are not fully correlated, as there are multiple different drivers behind both bond prices and the underlying benchmark curves, and the calculation of these spreads can vary significantly. As Hull et al. (2004) demonstrate, credit derivate markets, swap markets, and bond markets all use a slightly different benchmark curve in their pricing. Thus, the results from this study are not necessarily applicable to all of the other bond spreads described in chapter 3. G-spread was chosen for this study as it is not distorted by drivers in the swap or interbank market and it also showed the most similar behavior compared to CDS spreads, which are theoretically the purest measures of credit, as argued in chapter 3.

To summarize, the predictive power of CDS spreads and G-spreads are shown to be almost identical. Both credit spreads start to react approximately 4-6 months prior an upcoming rating event, but this is only true for negative events. For positive events, spreads show much less robust results, which is typical also in previous literature. Some uncertainty is related to the continuity of changing spread levels, as not all of the lagged monthly changes starting from 6 months prior and leading up to an event are significant. This makes it harder for an analyst or other interested party to predict possible rating changes, as the preceding monthly spread changes are not linear with respect to time. Individual monthly changes in spreads can be random or indicate no change in the near future, even if the rating will in fact change soon. A slightly more continuous pattern in spread levels were found when 2008 and 2009 was excluded from the CDS sample. This either indicates a paradigm change in credit spreads or credit ratings (certainly true to some extent), or demonstrates the fact that the 2008 financial crisis was so unexpected, that spreads had not much time to react before rating agencies started to announce multiple mass downgrades.

The results of this thesis complement many previous studies, such as Rodríguez et al. (2019) and Hull et al. (2004), but restricts the sample only to investment grade banks, demonstrating more clear and undebatable evidence for the field of bank risk analysis. Though the results support the use of market credit spreads in credit analysis and their superiority against credit ratings, a more refined model could still be developed for the prediction of rating changes. The magnitude of spread changes could be examined more thoroughly in order to determine, if a large enough relative change in credit spreads indicates an upcoming rating event regardless of the spread movements in surrounding months. As demonstrated in this study, not all of the monthly changes leading to an event are supporting the conclusion of an upcoming change in rating, meaning that there is some inconsistency in monthly lagged changes.

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